



Parallel implementation of FRAME – Filters, Random Fields and Maximum Entropy

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CSE633-Parallel Algorithms
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FRAME Objective

- Song C. Zhu, Yingnian Wu, David Mumford. “Filters, Random Fields and Maximum Entropy (FRAME): Towards a Unified Theory for Texture Modeling”, International Journal of Computer Vision, 1998.

- Texture modeling:

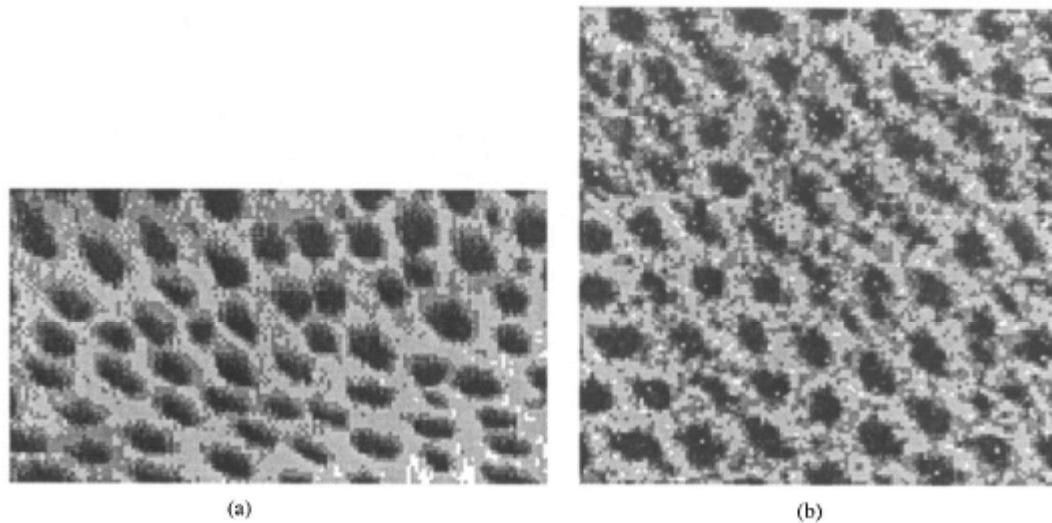
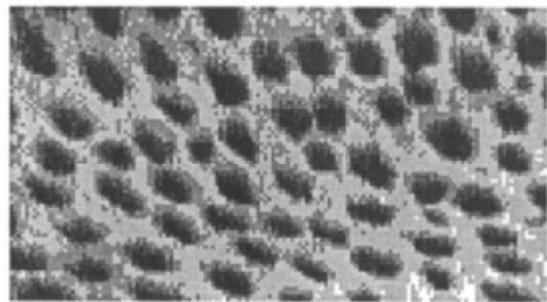


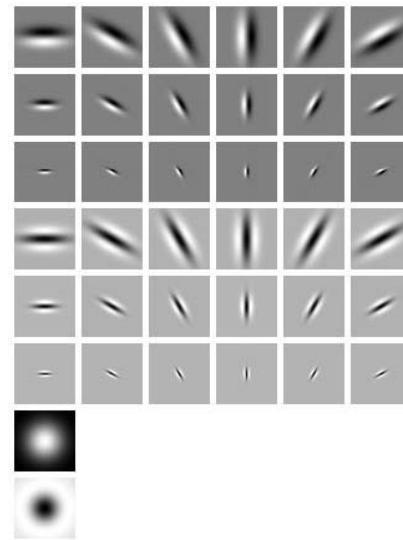
Figure 10. (a) The observed texture—cheetah blob, and (b) the synthesized one using six filters.

Method Overview

Input Image: \mathbf{I}^{obs}



Filters: $S_K = \{F^{(1)}, \dots, F^{(K)}\}$



Model:

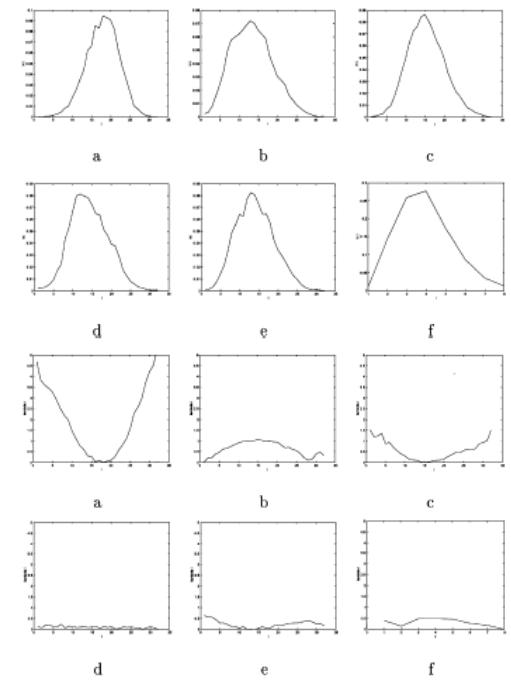
$$p(\mathbf{I}; \Lambda_K, S_K)$$

$$= \frac{1}{Z(\Lambda_K)} \exp \left\{ - \sum_{\alpha=1}^K \sum_{i=1}^L \lambda_i^{(\alpha)} H_i^{(\alpha)} \right\},$$

$$= \frac{1}{Z(\Lambda_K)} \exp \left\{ - \sum_{\alpha=1}^K \langle \lambda^{(\alpha)}, H^{(\alpha)} \rangle \right\}.$$

Histograms:

$$\{H^{\text{obs}(\alpha)}, \quad \alpha = 1, \dots, K\}.$$





Algorithm

Algorithm 1. The FRAME Algorithm

Input a texture image \mathbf{I}^{obs} .

Select a group of K filters $S_K = \{F^{(1)}, F^{(2)}, \dots, F^{(K)}\}$.

Compute $\{H^{\text{obs}(\alpha)}, \alpha = 1, \dots, K\}$.

Initialize $\lambda_i^{(\alpha)} \leftarrow 0, i = 1, 2, \dots, L, \alpha = 1, 2, \dots, K$.

Initialize \mathbf{I}^{syn} as a uniform white noise texture.

Repeat

Calculate $H^{\text{syn}(\alpha)}, \alpha = 1, 2, \dots, K$ from \mathbf{I}^{syn} , use it for $E_{p(\mathbf{I}; \Lambda_K, S_K)}(H^{(\alpha)})$.

Update $\lambda^{(\alpha)}, \alpha = 1, 2, \dots, K$ by Eq. (19),
 $p(\mathbf{I}; \Lambda_K, S_K)$ is updated.

Apply Gibbs sampler to flip \mathbf{I}^{syn} for w sweeps under $p(\mathbf{I}; \Lambda_K, S_K)$

Until $\frac{1}{2} \sum_i^L |H_i^{\text{obs}(\alpha)} - H_i^{\text{syn}(\alpha)}| \leq \epsilon$ for $\alpha = 1, 2, \dots, K$.

Algorithm 2. The Gibbs Sampler for w Sweeps

Given image $\mathbf{I}(\vec{v})$, flip_counter $\leftarrow 0$

Repeat

Randomly pick a location \vec{v} under the uniform distribution.

For $\text{val} = 0, \dots, G - 1$ with G being the number of grey levels of \mathbf{I}

Calculate $p(\mathbf{I}(\vec{v}) = \text{val} \mid \mathbf{I}(-\vec{v}))$ by
 $p(\mathbf{I}; \Lambda_K, S_K)$.

Randomly flip $\mathbf{I}(\vec{v}) \leftarrow \text{val}$ under $p(\text{val} \mid \mathbf{I}(-\vec{v}))$.
flip_counter \leftarrow flip_counter + 1

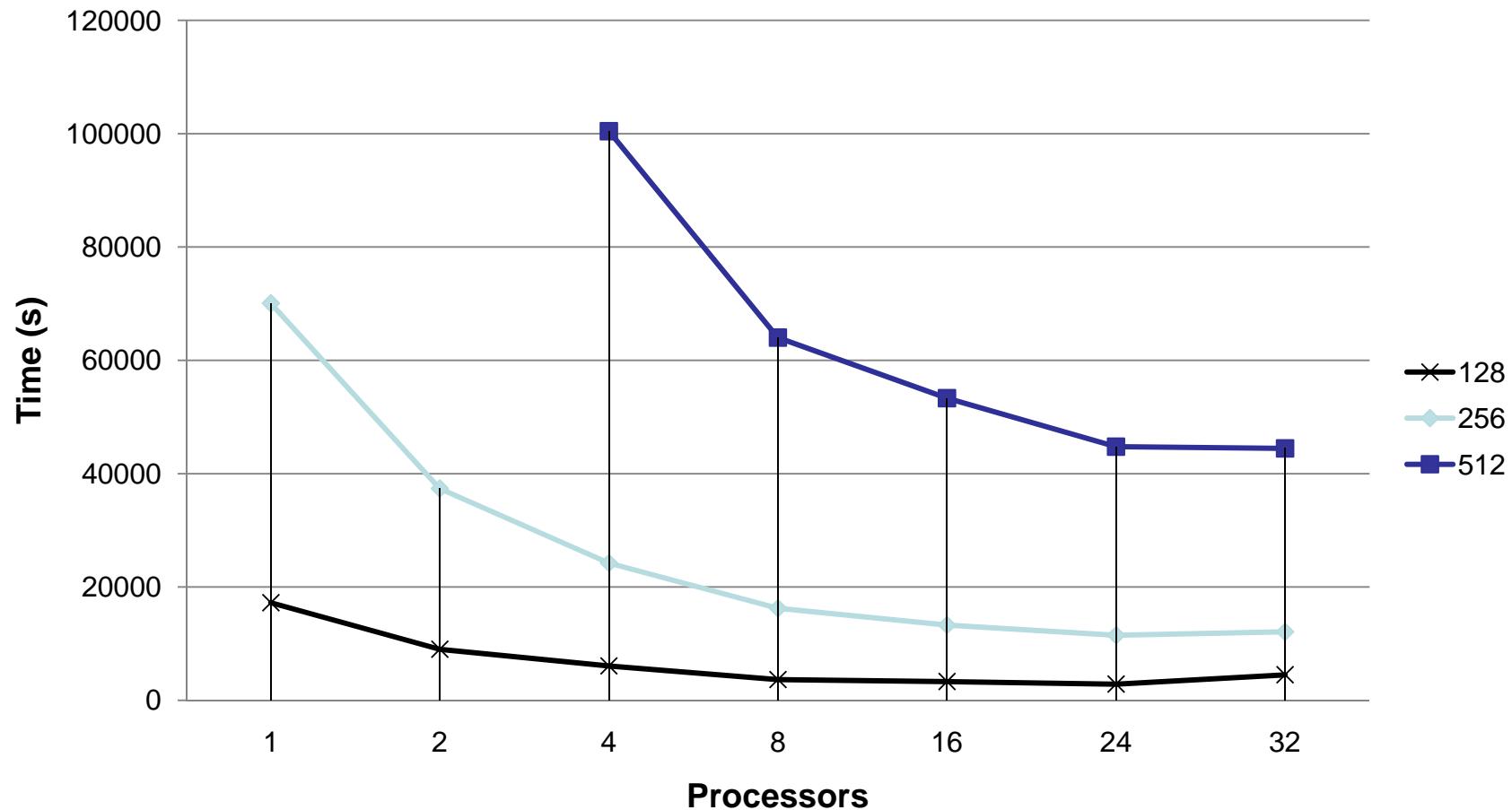
Until flip_counter = $w \times M \times N$.



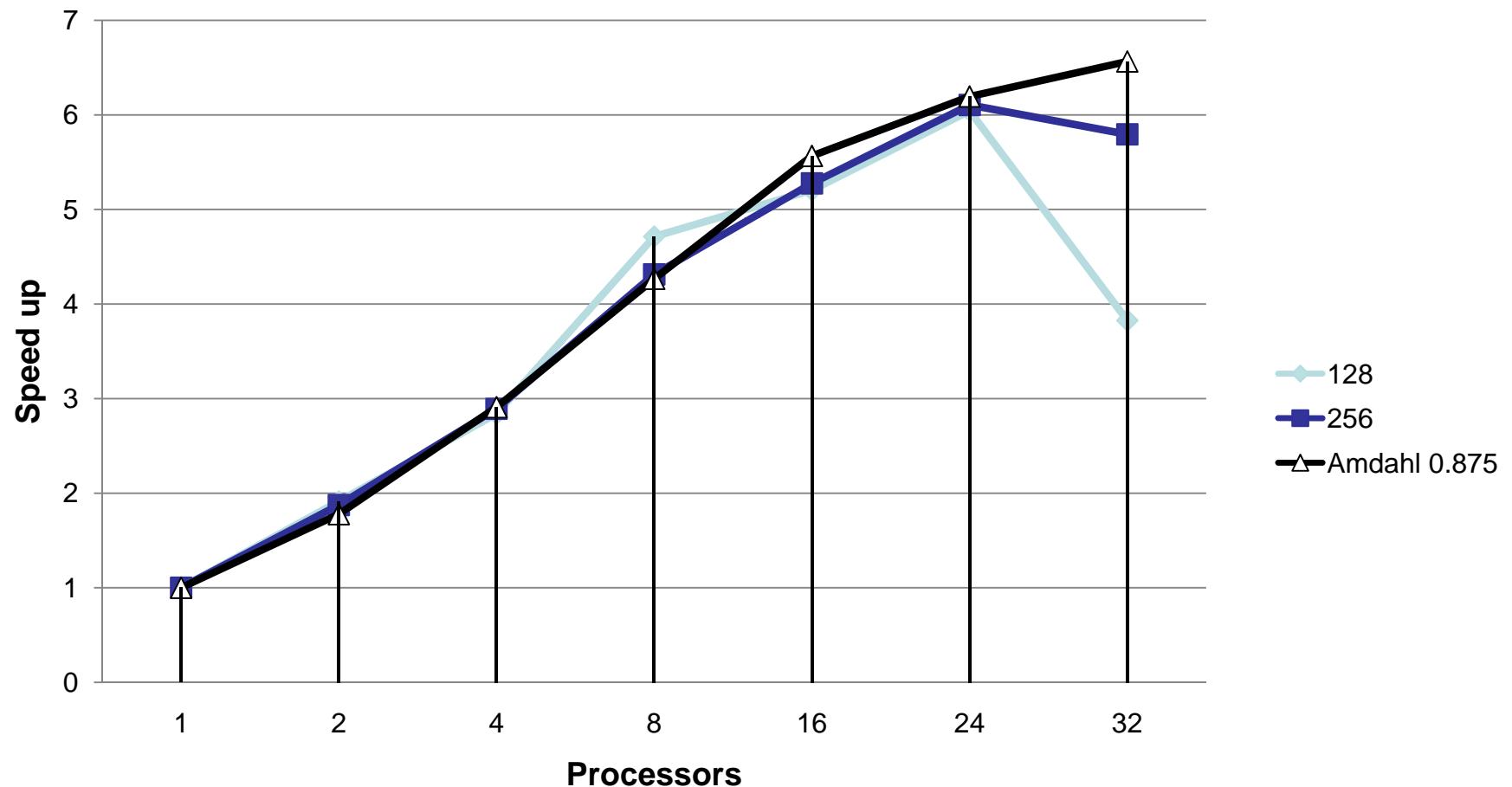
Implementation Issues

- Algorithm 2 (Gibbs sampler) was parallelized.
 - Work shared in the “filter level”
 - So far I have used 24 filters
- Parallelized for shared memory machines using OpenMP
- Parallel region -> 87.5%
- MKL optimizations not running yet due to different versions of MKL in U2 and LENNON.

Running time for different image size

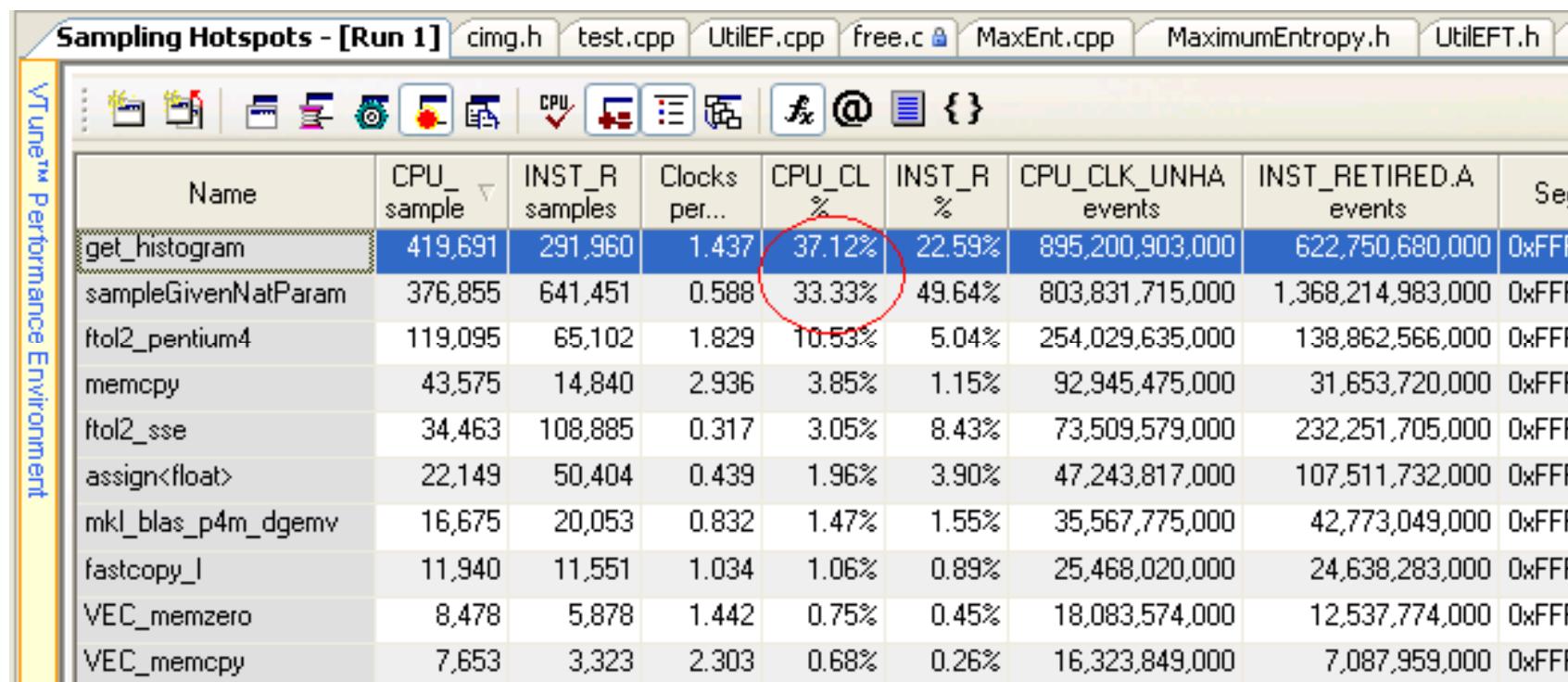


Speed up





Serial code profiling using Intel VTune





Still working on...

- Extend the use of MKL for more optimization
- Test with different input configurations.